

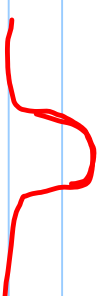
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Note Title

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$L_2$ -approximation: we minimize

$$\Phi(a, b) = \sum_{k=0}^m (ax_k + b - y_k)^2$$



If the error follows a normal probability distribution, then the minimization of  $\Phi$  produces a best estimate of  $a$  and  $b$ .

Using Calculus, at the minimum we have

$$\frac{\partial \Phi}{\partial a} = 0 \quad \text{and} \quad \frac{\partial \Phi}{\partial b} = 0$$

That is

$$\sum_{k=0}^m 2(ax_k + b - y_k)x_k = 0$$

$$\sum_{k=0}^m 2(ax_k + b - y_k)1 = 0$$

which are called the normal equations

Rewrite as

$$\left\{ \begin{array}{l} \left( \sum_{k=0}^m x_k^2 \right) a + \left( \sum_{k=0}^m x_k \right) b = \sum_{k=0}^m y_k x_k \\ \left( \sum_{k=0}^m x_k \right) a + \left( \sum_{k=0}^m 1 \right) b = \sum_{k=0}^m y_k \end{array} \right.$$

$$\underbrace{\left( \sum_{k=0}^m 1 \right)}_{(m+1)} b = \sum_{k=0}^m y_k$$

If we let  $P = \sum_{k=0}^m x^2$ ,  $q = \sum_{k=0}^m y_k$

$$r = \sum_{k=0}^m x_k y_k, \quad s = \sum_{k=0}^m x_k^2$$

Then the normal equation can be written as

$$\begin{cases} sa + pb = r \\ pa + (m+1)b = q \end{cases}$$

which is a  $2 \times 2$

$$\begin{bmatrix} s & p \\ p & (m+1) \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} r \\ q \end{bmatrix} \quad \begin{array}{l} \text{linear system} \\ \text{(Easy to solve!)} \end{array}$$

## Example

Find the linear least-squares solution for the following table of values

$x$	4	7	11	13	17
$y$	2	0	2	6	7

Plot the original data points and the line.

$$P = \sum_{k=0}^4 x_k = 4 + 7 + 11 + 13 + 17 = 52$$

$$Q = \sum_{k=0}^4 y_k = 2 + 0 + 2 + 6 + 7 = 17$$

$x$	$y$	$x^2$	$xy$	$y^2$
4	2	16	8	4
7	0	49	0	0
11	2	121	22	4
13	6	169	78	36
<u>17</u>	<u>7</u>	<u>289</u>	<u>119</u>	<u>49</u>
52	17	644	227	17

$$p = \sum_{k=0}^4 x_k = 52$$

$$q = \sum_{k=0}^4 y_k = 17$$

$$r = \sum_{k=0}^4 x_k y_k = 227$$

$$s = \sum_{k=0}^4 x_k^2 = 644$$

Hence

$$\begin{bmatrix} 644 & 52 \\ 52 & 17 \end{bmatrix} \begin{bmatrix} q \\ b \end{bmatrix} = \begin{bmatrix} 227 \\ 17 \end{bmatrix}$$

## Methode 1: Crammer's Rule

$$a = \frac{\det \begin{bmatrix} 222 & 522 \\ 17 & 5 \end{bmatrix}}{\det \begin{bmatrix} 644 & 522 \\ 52 & 5 \end{bmatrix}} = \frac{(222)(5) - (522)(17)}{(644)(5) - (52)^2} = \frac{251}{516} \approx \boxed{0.4866}$$

$$b = \frac{\det \begin{bmatrix} 644 & 222 \\ 52 & 17 \end{bmatrix}}{\det \begin{bmatrix} 644 & 522 \\ 52 & 5 \end{bmatrix}} = \frac{-856}{516} \approx \boxed{-1.659}$$

Best fit

$$y = \boxed{0.4862x - 1.659}$$

## Example

What straight line best fits the following data

x	1	2	3	4
y	0	1	1	2

In the least-squares sense?

x	y	xy	x <sup>2</sup>
1	0	0	1
2	1	2	4
3	1	3	9
4	2	8	16
$\Sigma$	4	13	30

$p =$

$$\begin{cases} 5a + pb = r \\ pa + (m+1)b = 2 \end{cases}$$

$$\begin{bmatrix} 30 & 10 \\ 10 & 4 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} 13 \\ 4 \end{bmatrix}$$

$$a = \frac{\det \begin{bmatrix} 13 & 10 \\ 4 & 4 \end{bmatrix}}{\det \begin{bmatrix} 30 & 10 \\ 10 & 4 \end{bmatrix}} = \frac{(2-40)}{120-100} = \frac{12}{20} = \frac{3}{5}$$

$$b = \frac{\det \begin{bmatrix} 30 & 13 \\ 10 & 4 \end{bmatrix}}{\det \begin{bmatrix} 30 & 10 \\ 10 & 4 \end{bmatrix}} = \frac{120-130}{120-100} = \frac{-10}{20} = -\frac{1}{2}$$



Least squares line:

$$y = \frac{3}{5}x - \frac{1}{2}$$

Another way of looking at the problem.

We want to determine the equation of a line of the form  $y = ax + b$

that fits the data best in the least squares sense.

Suppose we have four data points  $(x_i, y_i)$   $i = 1, 2, 3, 4$   
we get four equations

$$y_1 = ax_1 + b$$

$$y_2 = ax_2 + b$$

$$y_3 = ax_3 + b$$

$$y_4 = ax_4 + b$$

Remember as

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix}$$

$$A \vec{x} = \vec{b}$$

In general we want to solve a linear system

$$A \vec{x} = \vec{b}$$

where  $A$  is an  $m \times n$  matrix and  $m > n$

The solution coincides with the solution of the normal equations

$$A^T A \vec{x} = A^T \vec{b}.$$

This corresponds to minimizing

$$\|A \vec{x} - \vec{b}\|_2^2$$